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Investigation of squeeze cast process parameters effects on secondary dendrite arm spacing using statistical regression and artificial neural network models

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Abstract

The near net shape manufacturing capability of squeeze casting process have the potential to produce high dense components with refined micro-structure. However, squeeze cast micro-structure is influenced by large number of process variables such as squeeze pressure, time delay, pressure duration, die temperature and pouring temperature. In the present work, an attempt is made to develop the model by considering aforementioned process variables. Further, significant contribution of each process parameter on the secondary dendrite arm spacing is studied by using statistical regression tool. The mathematical relationship has been developed for secondary dendrite arm spacing was used to generate the training data artificially at random and tested with the help of few test cases. It is to be noted that the test cases chosen were different from training data. Scaled conjugate gradient, Levenberg-Marquardt algorithm and regression model predictions were compared. It is interesting to note that, all models were capable to make good prediction with an average of 5 percentage deviation. Levenberg-Marquardt algorithm outperforms in terms of prediction compared to other models in the present work. The reason might be due to the nature of error surface.

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Keywords: Squeeze casting process, LM20 alloy, Response surface plots, Secondary dendrite arm spacing and Artificial neural networks

1. Introduction

Aluminium silicon alloys widely used as casting material due to its inherent properties such as excellent fluidity,

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wettability, formability, high specific strength, good castability, shrinkage reduction, corrosion resistance, low thermal expansion co-efficient, wear resistance, excellent mechanical properties [1-2]. The silicon widely used in aluminium alloys might be due to the salient features such as low density, improves fluidity, reduce melting temperature, abrasion resistance, low cost and easily available. Addition of copper and magnesium are mandatory to improve the strength of the alloy [2]. In order to meet the stringent limitations of conventional casting process such as gas and shrinkage porosities, the research focussed on use of advanced squeeze casting processes which combines the features of both casting and forging processes. LM20 alloy belongs to the combination of Al-Si-Cu-Mg-Ni family. These combination alloys have salient features yields better casting characteristics [3], modifies silicon morphology [4], micro and macro structure [5] properties, refines dendritic structure [6] when processed using squeeze casting process.

Skolianos et al., (1997) made an attempt to study the effect of squeeze pressure on mechanical and micro-structure properties of squeeze cast AA6061aluminium alloy [6]. Fan et al., (2010) explored the effects of casting temperatures on ultimate tensile strengths and micro-structure properties such as grain size and secondary dendrite arm spacing (SDAS) of squeeze cast Al-Zn-Mg-Cu alloy [7]. Yue (1997) analyzed the effect of pouring temperatures and squeeze pressures at different squeeze casting conditions on the grain size structure of squeeze cast AA7010 wrought alloy [8]. Hajjari and Divandari (2008) investigated the effects of squeeze pressures on mechanical and micro-structure properties of squeeze cast wrought AA2024 alloy [9]. Senthil and Amirthagadeswaran, (2013) made an efforts to investigate the influencing squeeze casting process variables on mechanical, micro and macro-structure properties of squeeze cast AC2A alloy [10]. Maleki et al., (2009) considered the most influencing process parameters such as squeeze pressure, melt and die temperature to explore the effects on grain size, SDAS and aspect ratio of eutectic silicon particles [11]. Krishna (2001) reported high quality squeeze cast products are influenced by squeeze casting process variables and till date there is no universal standard available to obtain optimal process parameters to yield high quality squeeze cast parts [12]. ANNs proved as the cost effective tool in prediction, optimization, control, monitor, identification, modeling, classification and so on particularly in the field of casting and injection moulding processes [13]. Wang et al, (2011) made an attempt to predict the temperature difference of the squeeze cast part at different casting conditions utilizing with back propagation algorithm of ANNs [14]. Wang et al., (2013) utilized artificial neural networks to study the effects of squeeze cast process parameters on the solidification time of the squeeze cast hot die steel using procast simulation software [15]. From the above literatures it is confirmed that squeeze casting process parameters also decides the final cast structure, the quantitative information regarding the SDAS as a function casting variables are necessary for an industrialist to reduce the defects and ANNs can effectively map the complex non-linear relationship between the interplay of input-output parameters in various casting applications. The present work focused to explore the effects under both experimentally and simulation studies. An attempt made to experimentally investigate the final solidified structure using mechanical modification process parameters such as squeeze pressure (S_p), pressure duration (P_d), time delay in applying pressure (T_d), pouring (P_t) and die (D_t) temperatures and develop the mathematical model using regression analysis technique. To avoid costly manufacturing in analyzing the effects, artificial neural network simulation model using levenberg-marquardt (LM) and scaled conjugate gradient (SCG) algorithms was developed and the performance in predictions was compared with experimentally measured SDAS values.

1.1. Materials and Methods

In the present work LM20 aluminium alloy was used as a casting material due to its interesting features such as free from hot tear, excellent fluidity, pressure tightness, wear and corrosion resistance properties. These distinguished features of this alloy made LM20 alloy have wide applications in marine castings, meter cases, street lightings, casting subjected to atmospheric conditions, automobile office and domestic equipments. H13 hot die steel was used as the die material to withstand high pressure applied during solidification and normally in squeeze casting process dies were exposed to several number of thermo-mechanical cycles. Hence the dies were heat treated to an hardness of 45-48 R_c to withstand thermal fatigue, cracking, corrosion, erosion and indentation [16]. The quantitative chemical examination performed using optical emission spectrometer (OES) for the casting and the die material to know the exact chemical composition used in the present experimental study. The result of chemical analysis of LM20 alloy as per references standard ASTM E1251-07 the obtained chemical composition of LM20 alloy is Si-

10.41%, Fe-0.287%, Cu-0.177%, Mn-0.526%, Mg-0.175%, Cr-0.017%, Ni-0.016%, Zn-0.347%, Ti-0.175%, and Al-87.84% by weight. The obtained chemical composition of H13 hot die steel such as C-0.39%, Mn-0.38%, Si-1%, Cr-4.9%, P-0.019%, Mo-1.17%, V-0.79%, Fe-90.91% by weight.

2. Experimental details & plan

H13 hot die steel was used to prepare the punch and the cylindrical die cavity. The punch is fitted at the middle of the cross head and the die was placed on the base plate of 40 tonne universal testing machine. Mica strip electrical heater was used to pre-heat both die and punch. J-type thermocouple connected to digital indicators was used to accurately control the die temperatures. Electrical resistance crucible furnace was used to prepare the melt. K-type thermocouple connected to digital indicator was used to measure the temperature of the melt before pouring. Cover flux was used to clean the melt and hexachloroethane tablet was used as degasser to remove absorbed or dissolved gases in the melt. The measured quantity of the prepared melt is poured into the pre-heated cylindrical die cavity and punch was then brought to come in contact with the melt to apply pressure. Pressure is applied for predetermined time, the punch was withdrawn and casting was ejected from the die surface. The choice of process parameters considered in the present study is based on some pilot experiments conducted in the lab and from the available literatures. The experiments conducted by varying one parameter at a time and keeping the rest at their respective middle level. The process parameters and the respective levels used in the current study are shown in table 1.

Table 1. Process parameters and their respective levels

Process parameters	Units	Level-1	Level-2	Level-3	Level-4	Level-5
Squeeze pressure, (S_p)	MPa	0.1	50	100	150	200
Pressure duration, (D_p)	S	10	20	30	40	50
Time delay, (T_d)	S	03	05	07	09	11
Pouring temperature, (P_t)	˚C	630	660	690	720	750
Die temperature, (D_t)	˚C	100	150	200	250	300

3. Microstructure specimen preparation and examination

Micro-structure examination performed on the squeeze cast specimens of 15 mm sample size thickness. The sectioned surface is initially grounded using belt grinder, followed by series of silicon carbide papers with increasing fineness. Continuous circulation of water was maintained during grinding. Disc polisher using 400 mesh Al_2O_3 powder, 1000 mesh SiC powder with water, finally with diamond paste and hyfin liquid until scratch free surface was observed. The prepared samples were cleaned with soap solution followed by alcohol and dried. The samples were etched with kellers reagent (2.5% HNO_3+ 1.5% HCl + 1%HF + 95%H_2O) solution to reveal the micro-structure. The prepared samples were viewed using optical microscope and the obtained images were used to measure the secondary dendrite arm spacing (SDAS).

4. Regression Analysis

Regression analysis is a statistical tool helps the researcher/investigator to explore the effects, analyze the behaviour and to obtain the optimum process parameter setting for the corresponding process variables [17]. In the present work regression analysis is adopted to develop the relationship between the squeeze cast process variables and the measured secondary dendrite arm spacing. The data used to develop the regression equation is shown in table 3 and the obtained regression equation is shown in equation (1). Response surface plots obtained from the minitab software was used to analyse the effects of squeeze cast process variables on the measured SDAS. Significant test was conducted to know the effects, contributions and the significance of squeeze cast process variables towards the improvement for SDAS values. The terms used in table 2: is as follows [18], Coef refers to coefficients used in equation (1) for representing the relation between the squeeze cast process variables and the measured SDAS. SE Coef stands standard error for the estimated coefficients; smaller the value more precise will be the co-efficient. The ratio of coefficient and the corresponding standard error results in T-value. T-value for the independent variable can be used to test, whether the predictor significantly affects the measured response. The p-value is the minimum value for a pre-set level of significance, at which the hypothesis of equal means for a given factor can be rejected. The obtained results of significance test were evaluated at 95% confidence level and all the squeeze cast process variables were significant for the measured SDAS shown in Table 2. All the individual process variables shown less than 0.05 p-values indicate all parameters are significant impact on SDAS. From the ANOVA table it can be seen that all the square, linear and regression terms were less than 0.05 p-values, this indicates all terms are significant.

Table 2. Significance tests and ANOVA test results for Secondary dendrite arm spacing (SDAS)

Significance test of squeeze cast process parameters				
Term	Coef	SE Coef	T	P
Constant	313.45	93.344253	3.358	0.008
T_d	3.71889	0.6136782	6.06	0
D_p	-0.318161	0.1060537	-3	0.015
S_p	-0.120364	0.0358013	-3.362	0.008
P_t	-0.632729	0.2628704	-2.407	0.039
D_t	-0.22336	0.027906	-8.004	0
T_d*T_d	-0.144949	0.0428463	-3.383	0.008
P_d*P_d	0.0023871	0.0017137	1.393	0.197
S_p*S_p	0.0001988	0.0001354	1.468	0.176
P_t*P_t	0.0004023	0.0001904	2.113	0.064
D_t*D_t	0.0005135	6.855E-05	7.49	0

ANOVA for Secondary dendrite arm spacing						
Source	DF	Seq. SS	Adj. SS	Adj. MS	F	P
Regression	10	347.458	347.458	34.7458	51.7	0
Linear	5	282.981	273.589	54.7178	81.42	0
Square	5	64.477	64.477	12.8954	19.19	0
Residual Error	9	6.048	6.048	0.6721		
Total	19	353.506				

$$SDAS = 313.45 + 3.71889T_d - 0.318161D_p - 0.120364S_p - 0.632729P_t - 0.22336D_t - 0.144949T_d^2 + 0.00238712D_p^2 \\ +0.0001987998S_p^2 + 0.000402338P_t^2 + 0.000513454D_t^2 \quad (1)$$

4.1 Secondary dendrite arm spacing measurement

SDAS measurement is of paramount importance in deciding the mechanical properties and is influenced by the major parameters namely liquid metal treatment, solidification time, temperature gradient between the metal-mould interfaces and alloy chemical composition. Linear intercept method was used for the measurement of SDAS via image analysis software. The quantification of SDAS is done by drawing the lines measuring the distance between the adjacent sides on the longitudinal part of a primary dendrite as a function of the distance from the dendrite tip [19]. The total 21 samples were prepared for micro-structure observations and three optical micro-graph images were taken on each sample at different locations and at least five measurement values were taken in each location and the obtained average values is presented in table 3.

Table 3. Experimental observations of measured SDAS

Exp. No	Squeeze cast process parameters					Secondary dendrite arm spacing (μm)			Mean SDAS (μm)
	T_d	D_p	S_p	P_t	D_t	$SDAS_1$	$SDAS_2$	$SDAS_3$	SDAS
1	3	30	100	690	200	38.797	36.514	35.889	37.067
2	5	30	100	690	200	38.77	42.873	41.314	40.986
3	7	30	100	690	200	47.477	46.130	44.461	46.023
4	9	30	100	690	200	49.833	49.050	48.346	49.076
5	11	30	100	690	200	49.505	50.106	50.141	49.917
6	7	10	100	690	200	51.574	49.093	49.734	50.134
7	7	20	100	690	200	48.841	48.610	46.389	47.947
8	7	40	100	690	200	44.844	44.173	43.269	44.095
9	7	50	100	690	200	43.656	42.511	43.771	43.313
10	7	30	50	690	200	52.353	48.402	49.558	50.104
11	7	30	150	690	200	42.178	41.793	40.997	41.656
12	7	30	200	690	200	39.743	40.192	39.743	39.893
13	7	30	100	630	200	52.588	50.923	52.094	51.868
14	7	30	100	660	200	48.402	48.610	47.241	48.084
15	7	30	100	720	200	44.091	41.796	42.140	42.676
16	7	30	100	750	200	43.359	43.755	41.728	42.947
17	7	30	100	690	100	52.953	52.497	51.540	52.330
18	7	30	100	690	150	50.787	48.559	48.440	49.262
19	7	30	100	690	250	47.214	46.869	47.195	47.097
20	7	30	100	690	300	49.559	49.053	48.148	48.920
21	--	---	0.1	690	200	58.589	59.978	59.793	59.453

4.2 Response surface plots

Response surface plots obtained from the Minitab software was used to visualize graphically the relationship between the squeeze cast process variables and the SDAS. The surface plots obtained for the response-SDAS by varying two parameters and keeping the rest at the middle levels was shown in Figure 1. The following observations made from the surface plots are,

1. Fig. 1(a) and (b) depicts the response surface plots of the effects of two process variables namely time delay in pressurization with respect to the duration of pressure application and squeeze pressure respectively. The surface plots seen to be almost flat indicates a strong linear relationship exist between the process variables and the SDAS values. At low time delay in pressure application and high squeeze pressure and pressure duration yields lower SDAS values because, at low time delay the metal have enough fluidity and the applied squeeze pressure for longer duration forces the molten metal close enough to the die cavity by eliminating all possible gasses results in increase the heat transfer coefficient yields fine dendrite arm spacing values.

2. Fig. 1 (c) shows SDAS values has adverse effects with time delay and die temperature and lower SDAS values obtained at low time delay and middle level of die temperature. Low time delay and low die temperature the pre-mature solidification takes place before the pressure is applied due to existence of large temperature difference between the die and the metal temperature and low time delay and high die temperature keeps the fluidity of the metal for longer duration results in shrinkage in the casting, possibility of the miss runs and in addition cycle time also increases leads to higher SDAS values.

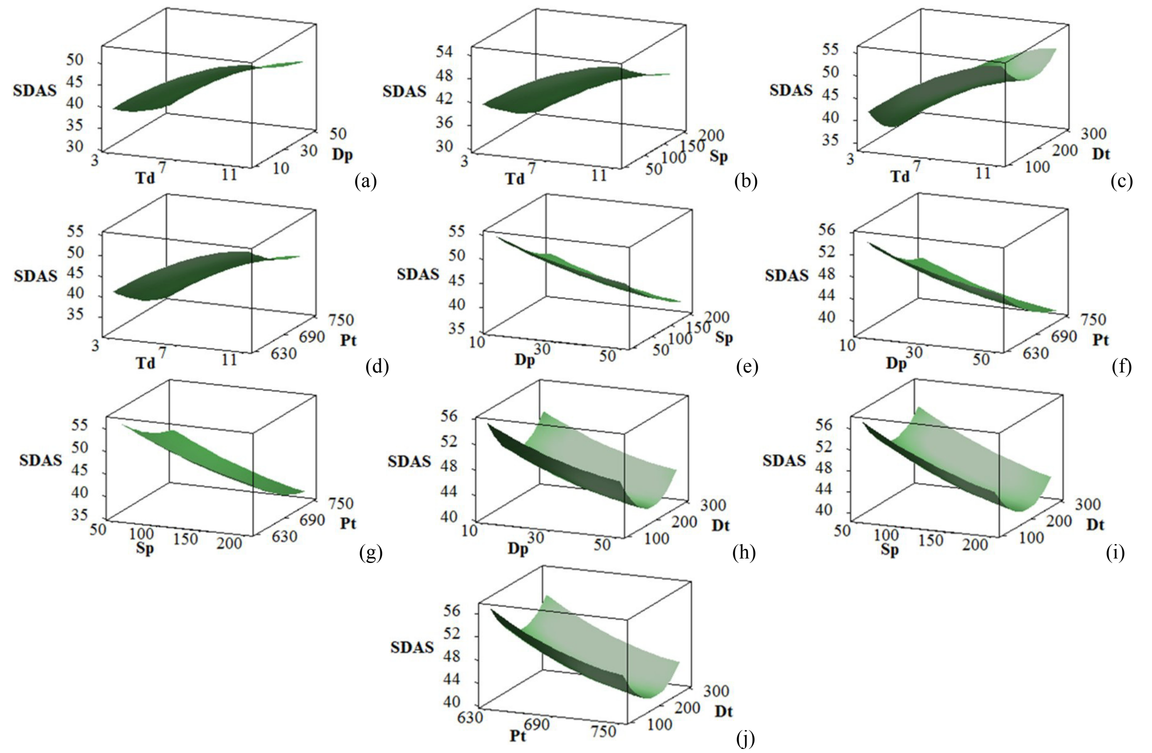
3. Time delay in pressurization and pouring temperatures has shown slight curvature with respect to SDAS values as shown in Fig. 1 (d). Fine dendrite spacing obtained at time delay of 3 seconds and pouring temperature of about 660 to 720˚C. However the effect of pouring temperatures is negligibly small compared to the die temperature shown in Fig. 1 (c).

4. The effect of pressure duration with respect to the squeeze pressure and the pouring temperature shown linear relation with the SDAS values shown in Fig. 1 (e) and (f). High applied pressure increases the melting point of the alloy and pushes the molten metal close to the die surface and not allowing the metal to pull out from the die surface at longer pressure duration keeps the metal close to die cavity until the complete solidification takes place results in finer dendrite arm spacing values, however negligible improvement after 40 seconds of pressure duration was observed.

5. Pouring temperature with respect to the squeeze pressure shown linear relation with SDAS values as shown in Fig. 1 (g). Squeeze pressure contribution to yield low SDAS is more compared to the pouring temperature was observed. Increase/decreasing the pouring temperature shown small undesirable effect with respect to squeeze pressure on SDAS.

6. Die temperature shown quadratic effect with respect to increase in pressure duration, squeeze pressure, and pouring temperature on SDAS values shown in Fig. 1 (h), (i) and Fig. (j) respectively. In all figures minimum secondary dendrite arm spacing obtained at the approximately 200˚C die temperature. Increase in squeeze pressure and pressure duration results in improved SDAS values Fig. (h) and Fig. (i). However with respect to pouring temperature small increase in SDAS values after 720˚C might be due to the increase in solidification time.

Confirmation experiment: From the experimental study the optimum combination of squeeze cast process parameter levels were determined. The confirmation experiment was conducted corresponding to optimal process parameter setting and yielded the fine secondary dendrite arm spacing values for squeeze cast LM20 alloy shown in table 4 (Exp. No 22). The applied pressure of 200 MPa breaks the dendrite arms in to small particle size due to higher heat transfer rate shown in Fig. 2 (b). Fig. 2 (c) depicts dendrites with large arm spacing along with micro-shrinkage porosity in the gravity cast samples were clearly visualized. Fig. 2 (a) depicts the time delay of 3 seconds yields better results with smaller dendrite arm spacing values.



Figs1. Surface plots of secondary dendrite arm spacing with (a) time delay and pressure duration, (b) time delay and squeeze pressure, (c) time delay and die temperature, (d) time delay and pouring temperature, (e) pressure duration and squeeze pressure, (f) pressure duration and pouring temperature, (g) squeeze pressure and pouring temperature, (h) pressure duration and die temperature, (i) squeeze pressure and die temperature, and (j) pouring temperature and die temperature

Table 4.Comparison of measured SDAS with regression and ANN models prediction

Exp. No.	Squeeze Cast Process Parameters T_d	D_p	S_p	P_t	D_t	Mean SDAS (mm)	Levenberg-Marquardt Prediction	Absolute % Error	Scaled Conjugate Gradient Prediction	Absolute % Error	Regression Equation Prediction	Absolute % Error
1	3	30	100	690	200	37.067	36.694	1.0063	37.059	0.0216	36.798	0.7257
2	5	30	100	690	200	40.986	41.812	2.0153	40.880	0.2586	41.919	2.2764
3	7	30	100	690	200	46.023	45.771	0.5476	46.171	0.3216	45.729	0.6388
5	11	30	100	690	200	49.917	50.210	0.5870	50.235	0.6371	50.425	1.0177
6	7	10	100	690	200	50.134	50.225	0.1815	50.535	0.7999	50.098	0.0718
7	7	20	100	690	200	47.947	47.759	0.3921	48.250	0.6319	47.598	0.7278
9	7	50	100	690	200	43.313	43.227	0.1986	42.891	0.9743	42.418	2.0633
10	7	30	50	690	200	50.104	50.298	0.3872	50.259	0.3094	49.687	0.8322
11	7	30	150	690	200	41.656	42.238	1.3972	42.656	2.4006	42.489	1.9971
12	7	30	200	690	200	39.893	39.698	0.4888	39.758	0.3384	39.794	0.2482
13	7	30	100	630	200	51.868	51.869	0.0019	51.403	0.8965	51.256	1.1799
15	7	30	100	720	200	42.676	43.808	2.6525	42.957	0.6584	43.626	2.2261
16	7	30	100	750	200	42.947	42.569	0.8802	42.042	2.1072	42.812	0.3143
17	7	30	100	690	100	52.33	52.704	0.7147	53.193	1.6491	52.972	1.2268
18	7	30	100	690	150	49.262	47.954	2.6552	48.522	1.5022	48.111	2.3365
20	7	30	100	690	300	48.92	49.108	0.3843	49.799	1.7968	49.191	0.5539
Training- Mean absolute percent error (MAPE)								0.906		0.956		1.153
4	9	30	100	690	200	49.076	48.865	0.4299	48.486	1.2022	48.571	1.0290
8	7	40	100	690	200	44.095	44.328	0.5284	44.405	0.7030	44.261	0.3765
14	7	30	100	660	200	48.084	48.671	1.2208	48.629	1.1334	48.458	0.7778
19	7	30	100	690	250	47.097	46.885	0.4501	46.110	2.0957	46.156	1.9980
22	3	50	200	720	200	30.133	31.502	4.5432	32.947	9.3386	26.114	13.337
Testing-Mean absolute percent error (MAPE)								1.4535		2.8946		3.5038

Artificial Neural Network models: Artificial neural network models are proven to be the cost effective tool from the past few decades to map the complex non-linear relationship exists between the input-output variables. The model works based on the principle of our biological nervous system. In our biological nerve system there are large numbers of interconnected processing units referred as neurons. The neurons of one layer connected to the neighbouring layer through connection strength called as weights. The weights contain information about the input signal. The connection pattern thus formed within and between the adjacent layers is referred as network architecture. The squeeze cast process parameters and SDAS expressed as a function of input-output neurons in the input and output layer respectively. The choice of hidden neurons in the hidden layer is determined under experimentation based on the minimum mean squared value between the targeted and the neural network predicted value. Pure linear function is used in the input and output layer and tan-sigmoid activation function is used in the hidden layer. The batch mode of training was employed for both LM and SCG algorithm.16 patterns of the experimental data chosen randomly along with artificially generated 234 data patterns from the regression analysis was used to train the neural network and the network prediction accuracy was checked for the remaining 4 data points which was never experienced during the training process shown in table 4. Co-efficient of determination (R^2) and Mean absolute percentage error (MAPE) was used to check the model prediction accuracy for the test cases. The range of R^2 value always lies between zero and one. Higher R^2 value indicates strong co-relation exists between the actual and predicted values. If R^2 value is zero indicates there is no co-relation at all. The MAPE and R^2 was also calculated to ensure the prediction accuracy between the actual and the model predicted values shown in table 5.

Table 5. Summary results of the developed models

Algorithm	Response	Optimum Network Architecture (N_i-N_h-N_o)	MSE training set	Co-efficient of correlation determination (R^2)-Test cases	Mean Absolute Percentage Error (MAPE)
SCG	SDAS	5-23-1	0.009159	0.9913	2.8946
LM	SDAS	5-9-1	0.000125	0.9978	1.4535
Regression				0.9937	3.5038

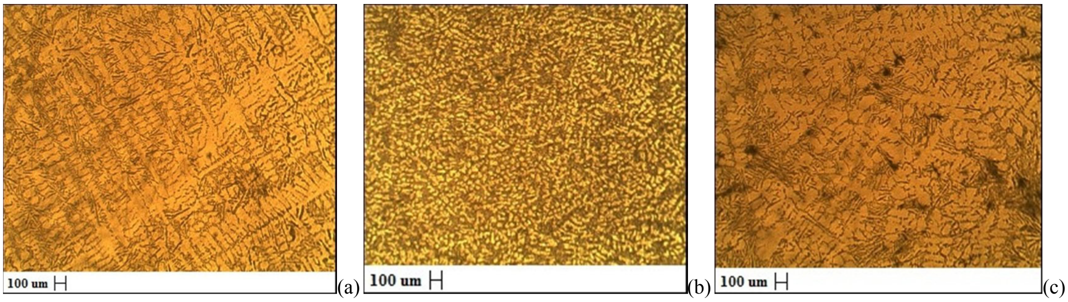


Fig. 2 Micro-structure at different casting conditions (a) Exp.No. 1 (Table 4), (b) Exp.No. 22 (Table 4) and (c) Exp.No. 21 (Table 3)

5. Conclusions

It is evident from the experimental work the cast micro-structure depends on the squeeze cast process variables during solidification and the following observations conclusions can be drawn from the current study,

1. Experiments performed by varying one process parameter individually and keeping the rest of the parameters at middle level. Increase in time delay before pressurization of the liquid metal shown increase in SDAS values due to reduced heat transfer co-efficient and non elimination of the gas completely between the metal mould interfaces.
2. Pressure duration and squeeze pressure shown strong linear relationship with SDAS values. Increase in squeeze pressure and pressure duration decreases the SDAS values because of improved contact area between the metal-die interfaces and the applied pressure for longer duration not allowed the metal to pull away from the die surface.
3. Die temperature is found to have non-linear relation with SDAS. It is interesting to know that, the combination of minimum die temperature and pouring temperature will result in maximum value of SDAS. Increase in die temperature will initially reduce SDAS value and found increasing after crossing mid value

of die temperature. However, increase in pouring temperature will reduce SDAS value. Further, pouring temperature is found to have more or less linear relation with SDAS.

4. Confirmation test was conducted for the optimal process parameter levels observed from the response surface plots namely, squeeze pressure at 200 MPa, pressure duration of 50 s, time delay of 3 s, pouring temperature at 720˚C and die temperature at 200˚C yield lower SDAS values. The mean SDAS value corresponding to optimal parameters is found to be equal to 30.133 µm.
5. Artificial neural network models were developed for the squeeze casting process. The developed models were trained with data collected from the experimental work and artificially generated data through regression equation. The trained neural network reduces the mean squared error (MSE) to a minimum value. The MSE value set for the training of NN was equal to 0.000125. It is to be noted that, lower value of MSE might require more number of iterations. However this will result in better training of NN. The accuracy of the developed network was tested for few test cases which are never experienced during the training process. LM algorithm outperforms the developed regression model and the SCG algorithm in the present work. Hence the developed ANNs can be used to predict and select the optimal process parameter setting by any novice user without having prior background knowledge about the squeeze casting process.

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